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COMPLETE SYSTEM ANALYSIS: QUANTITATIVE SYSTEM ANALYSIS, COMPUTER SIMULATION, AND SYSTEM OPTIMIZATION

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COMPLETE SYSTEM ANALYSIS: QUANTITATIVE SYSTEM ANALYSIS, COMPUTER SIMULATION, AND SYSTEM OPTIMIZATION*

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ABSTRACT

Many systems and processes in use today are quite complex, and experimentation regarding them is both difficult and expensive. For such systems or processes, mathematical solution for outputs in terms of inputs is usually not feasible, and computer simulation is often an effective and efficient complement to experimentation.

Complete system analysis is a general approach to the coordination of experimentation and computer simulation in the analysis and optimization of a system or process. In addition, it is somewhat novel in its approach. Three basic stages of complete system analysis are quantitative system analysis, computer simulation, and system optimization.

*This paper is the overview of a one-semester course, given by the authors for the Operations Research and Statistics Department of California State College at Long Beach. Complete system analysis and quantitative system analysis are discussed by Dr. Goodman; computer simulation, by Mr. Gainen; and system optimization, by Mr. Beum.

Quantitative system analysis transforms qualitative elements of the system into numerical form, and constructs a system model for relationships among component parts of the system. It is a comprehensive and definitive approach to model construction.

It is followed by computer simulation transforming the model, which is a mathematical representation of the system, into a simulation computer program, which is a computer representation of the system. Experimentation with the system may then be complemented by computer simulation of the system.

Finally, system optimization is accomplished by the optimization of a meaningful measure of system effectiveness. This optimization may be accomplished by mathematical techniques for simple systems. For complex systems, however, optimization requires iterative repetition of system experimentation and simulation, analysis, and improvement.

During the design of a complex system, the system does not yet exist and experimentation regarding it is impossible. The approach of complete system analysis then may be modified to yield complete system design, a meaningful framework for the utilization of computer simulation in the design of a complex system.

INTRODUCTION

Many systems and processes in use today are quite complex, and experimentation regarding them is both difficult and expensive. For such systems or processes, mathematical solution for outputs in terms of inputs is usually not feasible, and computer simulation is often an effective and efficient complement to experimentation.

When the model of the system or process is translated into a simulation computer program, the system or process and the effects of various factors upon it may be simulated. The accuracy and precision of the computer simulation increase as the accuracy and precision of the model increase.

There are four periods or phases in the life cycle of a system or process--research, development, operation, and replacement. In like manner, there are four periods or phases in the evolution of one's knowledge concerning an existing system or process--description, modeling, prediction, and control and optimization. Computer simulation yields appropriate results in all four periods of the life cycle, and in the latter three periods of the evolution of knowledge.

Complete system analysis is a general approach to the coordination of experimentation and computer simulation in analysis and optimization of a system or process. In addition, it is somewhat novel in its approach. Three basic stages of complete system analysis are quantitative system analysis, computer simulation, and system optimization.

Quantitative system analysis transforms qualitative elements of the system into numerical form, and constructs a system model for relationships among component parts of the system. It is a comprehensive and definitive approach to model construction.

A detailed structure is developed for the system by arranging system elements into an informative order. A numerical description then is defined for the detailed structure by associating a number with each ordered qualitative element. Component parts of the system are arranged into an informative and unifying order to form a general structure. To simplify the specification and estimation of a system model, related component parts are combined whenever feasible. A system model is constructed by specifying relationships among component parts in the general structure. The relationships are expressed as mathematical equations containing unspecified constants.

Computer simulation transforms the model, which is a mathematical representation of the system, into a simulation computer program, which is a computer representation of the system. Experimentation with the system may then be complemented by computer simulation of the system.

Finally, system optimization is accomplished by the optimization of a meaningful measure of system effectiveness. This optimization may be accomplished by mathematical techniques for simple systems. For complex systems, however, optimization requires iterative repetition of system experimentation and simulation, analysis, and improvement.

During the design of a complex system, the system does not yet exist and experimentation regarding it is impossible. The approach of complete system analysis then may be modified to yield complete system design, a meaningful framework for the utilization of computer simulation in the design of a complex system.

COMPLETE SYSTEM ANALYSIS

INTRODUCTION

Complete system analysis provides a logical and informative mechanism for augmenting experimentation with computer simulation. It supplies the framework of a program for constructing and estimating a model, developing a simulation computer program, validating the model and simulation computer program, performing experimental and simulation trials, and analyzing experimental and simulation data. It also includes iterative improvement of the system, and design of additional experimental and simulation trials.

An outline of complete system analysis is followed by an overview of it, and a brief discussion of it and it's modification for system design.

OUTLINE

Complete system analysis, as illustrated by Figure 1, is composed of eleven basic stages:

1. Quantitative system analysis to transform qualitative elements of the system into numerical form and to construct a model, with unspecified constants, or relationships among component parts of the system.
2. Experimental trial(s) to yield experimental data.
3. Model estimation to produce estimates of unspecified constants in the model from experimental data and available auxiliary data, and to perform a preliminary evaluation of the model's adequacy.
4. Simulation programming to construct a simulation computer program from the model.
5. Simulation trial(s) to yield simulation data.
6. Model and simulation data comparison to provide a validation (positive check) for the simulation computer program.
7. Experimental and simulation data comparison to provide a validation for the combination of model and simulation computer program.

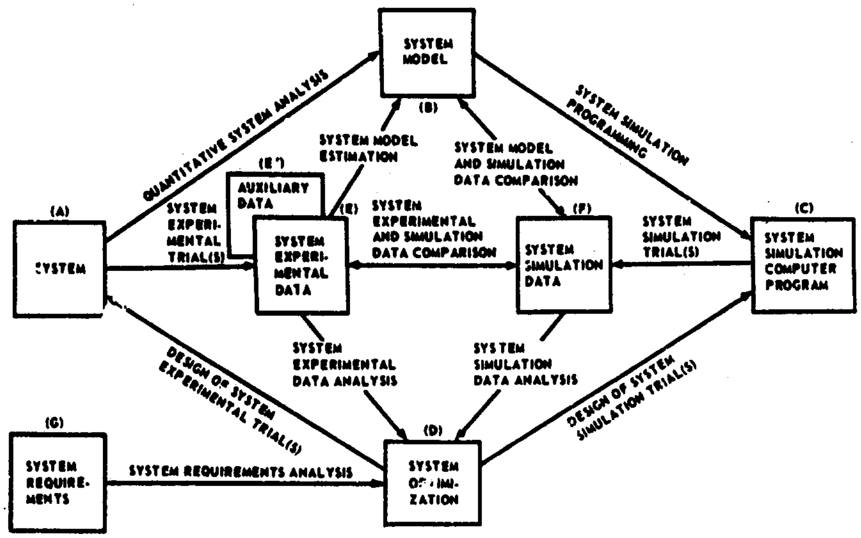


Figure 1. Complete System Analysis

8. Experimental and simulation data analysis to aid optimization by suggesting system improvement.
9. Optimization to improve the system and apply appropriate stages of complete system analysis to the improved system, in an iterative manner.
10. Design of experimental and simulation trials to implement optimization.
11. Requirements analysis to provide a basis for optimization, and design of experimental and simulation trials.

OVERVIEW

Complete system analysis, which is outlined above and graphically portrayed in Figure 1, may be viewed as a double diamond.

Its outer portion (composed of AB, AE, BC, CF, DA, and DC) contains those stages which precede the generation of data and are not data-based. Its inner

portion (composed of EB, BF, EF, ED, and FD) contains those stages which follow the generation of data and are data-based.

The model and simulation computer program are developed and validated by means of stages which comprise the upper portion of the double diamond (AB, AE, EB, BC, CF, BF, and EF). Analysis of data, and design of experimental and simulation trials to optimize the system, are performed by those stages which comprise the lower portion of the double diamond (ED, FD, DA, and DC).

Development of the model and design, performance and analysis of experimental trials are accomplished by those stages in the left-hand portion (AB, AE, EB, ED, and DA). Finally, the right-hand portion (BC, CF, BF, EF, FD, and DC) contains those stages concerned with developing and validating the simulation computer program, and with designing, performing and analyzing simulation trials.

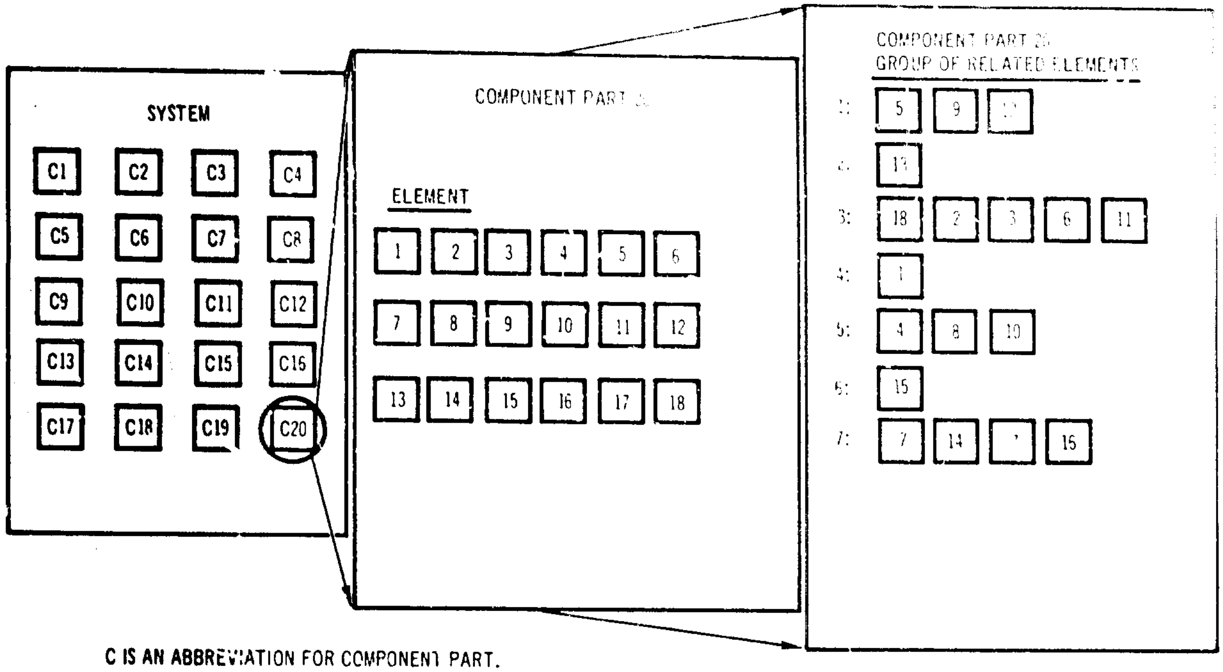
The inherent symmetry and simplicity of the double diamond make it a very meaningful and suggestive way in which to view complete system analysis.

DISCUSSION

Let the system be composed of components, the components contain component parts, and the component parts have elements. (Deeper levels of system composition could be considered, if necessary.)

The transformation of qualitative system elements into numerical form is accomplished in two steps:

1. A detailed structure for the system is developed by grouping the related elements in a component part, and arranging these groups and, to the extent feasible, elements within groups into an informative order. The grouping and arranging are based on a primary unifying characteristic of the elements in the component part, as determined from the elements themselves and the function of the component part (see Figure 2).
2. A numerical description of the detailed structure is defined by associating a number with each ordered qualitative element. The



C IS AN ABBREVIATION FOR COMPONENT PART.

Figure 2. Arrangement of Elements to Form a Detailed Structure

base point (zero) for a numerical scale is selected according to the primary unifying characteristic of the component part. With each element, there is associated a numerical value corresponding to its relative distance from the base point (see Figure 3).

Construction of a system model for relationships among component parts then is performed in the following three steps:

1. Groups of related component parts within a component--and components--are arranged into an informative and unifying order to form a general structure. To the extent feasible, the arrangement should be based on the desirable characteristic that a component part tends to influence only those component parts which follow it (see Figure 4).

2. Groups of related component parts are combined whenever feasible, to simplify the specification and estimation of a system model. Two of the simplest types of combinations are averages and products (see Figure 5).

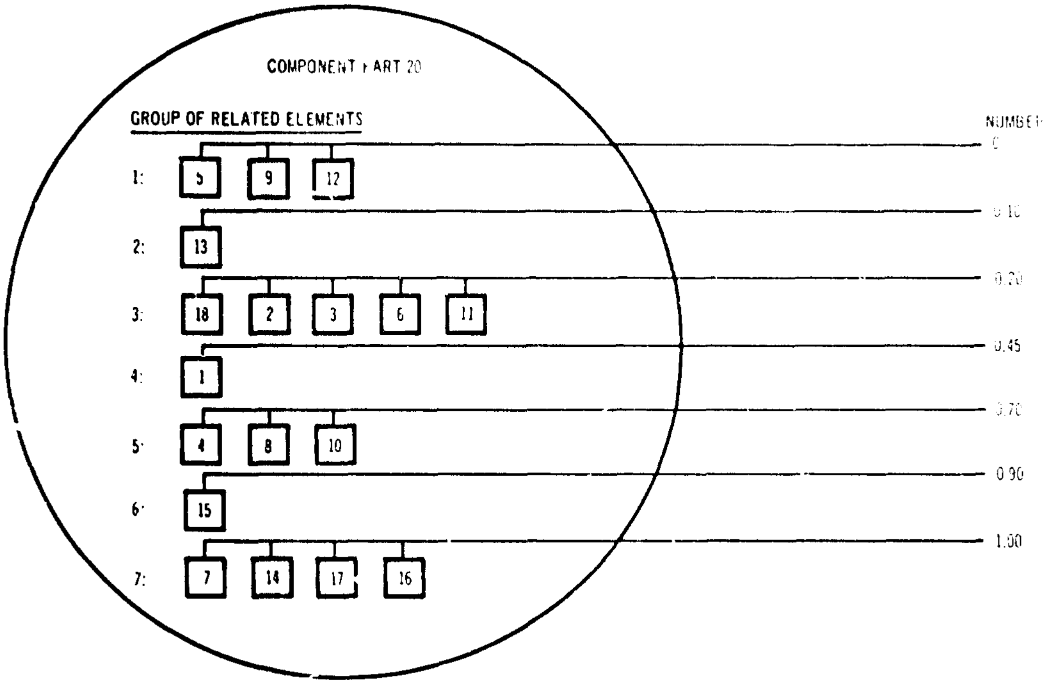


Figure 3. Association of a Number with Each Ordered Element

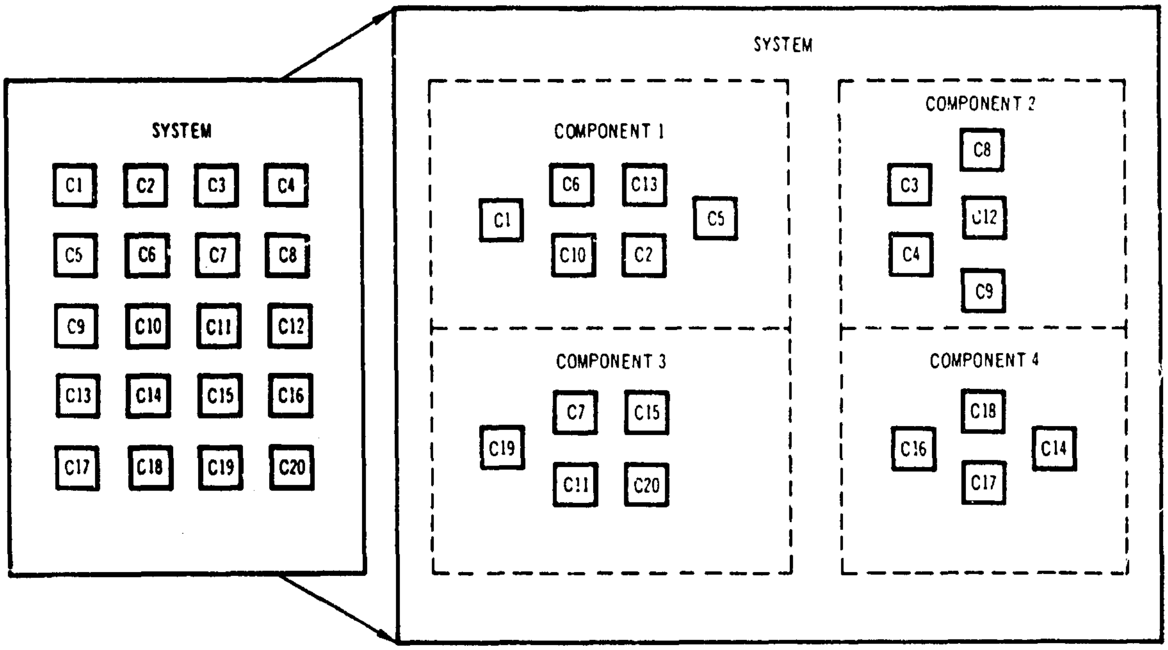


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Figure 4. Arrangement of Component Parts to Form a General Structure

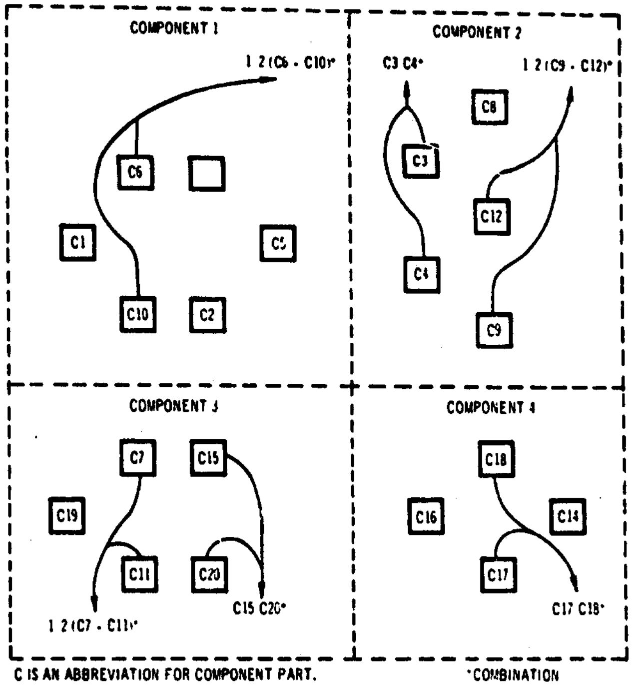

Figure 5. Combination of Component Parts

3. Relationships are specified among combinations of component parts in the general structure. These relationships comprise the system model, which is a mathematical representation of the system.

It is frequently both convenient and sufficiently accurate (for example, during exploratory research) to have the system model composed of linear relationships. The model should also contain random influences if the system contains them.

An application of quantitative system analysis to the flow of scientific and technical information (flow process) is summarized by Reference 1 and is presented in full by Reference 2.

The model becomes completely specified when values are assigned to its unspecified constants. The usual way to accomplish this is to estimate the constants from experimental data and available auxiliary data, by statistical

estimation techniques (for example, regression analysis). A system model which admits good estimators of its unspecified constants is preferable to a more exact one which admits only poor estimators.

A simulation computer program transforms the model's mathematical representation of the system into a computer representation of the system. Input data is required for the simulation computer program to produce a simulation trial.

Although frequently overlooked or ignored, validation should be provided for the model and simulation computer program. When the simulation computer program has been validated to assure that it adequately represents the system model, the combination of model and simulation computer program should be validated to assure that the combination adequately represents the system. The required comparisons, of the model and simulation data followed by that of experimental and simulation data, are performed by statistical testing techniques (for example, analysis of variance). When the system and model contain random influences, the same inputs may yield different sets of experimental and simulation data, and validation comparisons should take this randomness of the data into account. Experimental and simulation data analysis aids optimization by suggesting improvement of the system. The analysis is accomplished by both statistical estimation and testing techniques.

Since few systems cannot be improved, one of the most important stages is optimization through iterative improvement of the system and repetition of the appropriate stages of complete system analysis. The design of experimental and simulation trials is, of course, achieved by the techniques of statistical design of experiments.

Chapter 2 of Reference 3 describes the planning of computer simulation trials in a manner similar to that of complete system analysis.

During the design of a complex system, the system does not yet exist and experimentation regarding it is impossible. The system is replaced by

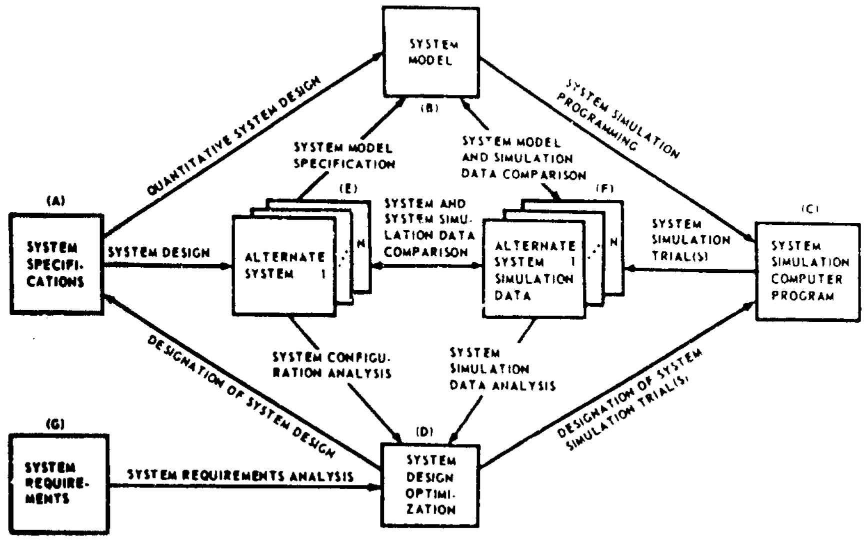

Figure 6. Complete System Design

system specifications; and system experimental data is replaced by alternate systems (system configurations) 1, 2, . . . , N. This modification of the approach of complete system analysis yields a meaningful framework for the utilization of computer simulation in the design of a complex system (see Figure 6.). It is called complete system design.

The Appendix presents a graphic summary of complete system analysis (Figures A-1 through A-8) and complete system design (Figures A-9 through A-16).

QUANTITATIVE SYSTEM ANALYSIS

INTRODUCTION

A vast majority of knowledge in the physical sciences, and an increasing amount in the behavioral and life sciences, is based upon models, of which many are mathematical. Mathematical and statistical operations begin with the assumption or existence of these models. To the author's knowledge, relatively little comprehensive and definitive work has been published on the modus operandi of their construction; even less has been published on construction for systems with elements which are inherently qualitative, rather than quantitative. Model construction is more an art than a science.

System analysis could accomplish part of the model construction by providing a structure for the system. However, it remains for quantitative system analysis to complete the model construction by transforming qualitative system elements into numerical form, and by specifying relationships among component parts of the system. Quantitative system analysis, although in somewhat preliminary form at present, is a comprehensive and definitive approach to the modus operandi of model construction.

A summary of quantitative system analysis has been given in the discussion of complete system analysis. It is described here in more detail.

References 1 and 2 contain an informative example of the application of quantitative system analysis to the flow of scientific and technical information (flow process). This application is summarized by Reference 1 and is presented in full by Reference 2. It is briefly introduced below. Pertinent tables from Reference 2 illustrate the description which follows.

The Department of Defense (DOD) has sponsored the DOD User-Needs Study to investigate, by means of a survey, the flow process within DOD (Phase I)

and the defense industry (Phase II). Phase II surveyed a representative sample of 1, 500 from a population of approximately 120, 000 engineers, scientists and technical personnel. These personnel were employed by 73 companies, 8 research institutes and 2 universities that are defense contractors.

An Interview Guide was employed to monitor the flow process by means of questions exploring the component parts of that process. Sixty-three questions were asked regarding the USER of scientific and technical information, his most recent scientific or technical TASK, his general UTILIZATION of information centers and services, and the SEARCH AND ACQUISITION process for information specifically related to the task. Responses to 55 of these questions are qualitative.

The components of the flow process are USER, TASK, UTILIZATION, and SEARCH AND ACQUISITION. Questions are the component parts, and question responses are the elements.

The two major parts in the description of quantitative system analysis are (1) transformation of qualitative system elements into numerical form, and (2) construction of a model for relationships among system component parts. The former contains development of a detailed structure for the system, and definition of a numerical description for the detailed structure; the latter contains development of a general structure for the system, combination of related component parts in the general structure, and specification of a system model for relationships among component parts.

TRANSFORMATION OF SYSTEM ELEMENTS

As noted above, the transformation of qualitative system elements into numerical form is performed by the development of a detailed structure and the definition of a numerical description for that detailed structure.

Development of a Detailed Structure

A detailed structure for qualitative system elements is developed to serve as the basis for the transformation of these elements. In addition, the detailed structure brings the local aspects of the system into focus and provides a foundation for a general structure. This detailed structure is formed by an informative arrangement of elements.

The first step is to specify a primary unifying characteristic of the elements in a component part. This element characteristic should be determined from not only the elements themselves, but also the function of the component part.

The next step is to collect into groups those elements which are related by the element characteristic. According to this characteristic, an ordering is then arranged for groups and, to the extent feasible, for elements within groups. All elements in a component part may be arranged into one ordering if all elements within each group may be arranged into an ordering. According to the element characteristic, an element or group of elements is more similar to elements or groups of elements which are closer to it in the arrangement, than to those farther away.

Depending on the implications of the element characteristic, there are three types of detailed structure:

1. Visible structure, explicitly implied by the element characteristic.
2. Partically visible structure, implicitly implied by the element characteristic.
3. Invisible structure, not implied at all by the element characteristic.

A visible structure is obvious, and possesses no flexibility. A partially visible structure is apparent, but possesses some flexibility. An invisible structure must be inferred, and possesses considerable flexibility. The position of elements in the arrangement is meaningful in a visible structure,

and indicative in a partially visible structure, but only descriptive in an invisible structure.

Examples of visible, partially visible, and invisible structure in the flow process application are given in Tables 1 through 3, respectively. For the tables, arabic numerals in parentheses--(1), (2), and so forth--indicate the ordering in the Interview Guide; while roman numerals--I, II, and so forth--indicate the ordering in the corresponding detailed structure. The numerical description scale is included in the tables.

Definition of a Numerical Description

When the detailed structure is developed, its numerical description is appropriate. By associating a number with each ordered qualitative element, the numerical description provides a more exact differentiation among the elements within a component part; and it enables estimation of the system model, which is composed of relationships among component parts. The numerical description also represents the system in a form to which a large variety of numerical techniques may be applied.

According to the element characteristic, the base point (zero) for a numerical scale is selected. With each element, there is associated a numerical value corresponding to its relative distance from the base point.

To standardize the numerical description, a negative integer, zero or positive integer is associated with each ordered qualitative element whenever feasible. Zero is employed when it is meaningful to consider the element to be null, and a negative integer is employed when it is meaningful to consider the element as opposite in direction to most of the elements. Variable spacing between the associated numbers indicates that the elements exhibit variable similarity, or distance from each other, according to the element characteristic. The same number is associated with two elements in a component part if--and only if--the two elements are in the same group of

Table 1
VISIBLE STRUCTURE

Question 58: User's Equivalent Government Service (GS) Rating*			
		Informative Order	Scale
I	(01)	GS-6 (under 6,000)	0.07
II	(02)	GS-9 (6,000 - 7,999)	0.15
III	(03)	GS-11 (8,000 - 10,249)	0.23
IV	(04)	GS-12 (10,250 - 11,999)	0.31
V	(05)	GS-13 (12,000 - 13,999)	0.39
VI	(06)	GS-14 (14,000 - 16,499)	0.46
VII	(07)	GS-15 (16,500 - 18,999)	0.54
VIII	(08)	GS-16 (19,000 - 20,999)	0.61
IX	(09)	GS-17 (21,000 - 23,999)	0.69
X	(10)	GS-18 (24,000 - 26,999)	0.77
XI	(11)	Sp A (27,000 - 29,999)	0.85
XII	(12)	Sp B (30,000 - 34,999)	0.92
XIII	(13)	Sp C (over 35,000)	1.00

*The element characteristic is equivalent GS rating.

related elements, and the elements within that group cannot be arranged into an ordering (that is, are the same distance from the base point).

The association of a number with each qualitative element in a component part associates a scale of possible numerical values with the component part. Then all numerical values in the scale are divided by the largest one in absolute value, so that the scale is normalized to between -1 and 1.

The value of the numerical description is meaningful for elements in a visible structure, and indicative for elements in a partially visible structure, but only descriptive for elements in an invisible structure. Examples are again provided by the flow process application in Tables 1 through 3.

Table 2

PARTIALLY VISIBLE STRUCTURE

Question 14: First Source for Information*

		Informative Order		Scale
I	(01)	Received with task assignment		0.00
II	(04)	Recalled it		0.05
III	(09)	Searched own collection		0.10
IV	(19)	Respondent's own action		0.15
V	(03)	Assigned subordinate to get it		0.20
VI	(05)	Asked a colleague		0.25
VII	(02)	Asked my supervisor		0.30
VIII	(08)	Requested search of department files		0.35
IX	(06)	Asked an internal company consultant		0.45
X	(10)	Searched company technical information center	**	0.50
X	(07)	Requested library search	**	0.50
XI	(15)	Requested data from vendor, manufacturer, or supplier	**	0.60
XI	(14)	Searched vendor, manufacturer, or supplier sources	**	0.60
XII	(11)	Searched an outside library		0.70
XIII	(18)	Asked an external consultant or expert		0.80
XIV	(13)	Requested search of a DOD Information Center	**	0.90
XIV	(12)	Searched a DOD Information Center	**	0.90
XV	(17)	Asked customer		1.00

* The element characteristic is distance from the user.

**In the analysis, no distinction is made between the two responses in this group of related responses.

Table 3

INVISIBLE STRUCTURE

Question 27: Desired Layout of Information Media*

	Informative Order		Scale
I	(14)	Recall	0.00
II	(13)	Telephone conversation	0.06
III	(11)	Group discussion	0.12
IV	(04)	Photographs	0.19
V	(03)	Graphics (diagrams, drawings, schematics, flow charts, graphs, maps)	0.25
VI	(02)	Tables or lists	0.31
VII	(01)	Narrative text	0.37
VIII	(18)	Narrative text and tables or lists	0.44
IX	(09)	Graphics and lists	0.50
X	(08)	Photographs and text	0.56
XI	(07)	Graphics and text	0.63
XII	(16)	Graphics, text, and oral	0.69
XIII	(17)	Graphics, text, oral, and recall	0.75
XIV	(12)	Informal briefing, with chalk or pencil drawings	0.82
XV	(05)	Microfilm - microfiche	0.88
XVI	(06)	Slides or motion pictures	0.94
XVII	(10)	Formal briefing or lecture	1.00

*The element characteristic is formality.

A detailed structure suggests its own numerical description when the elements in a component part have been properly arranged. For a more refined analysis, a numerical description could be altered to improve the linearity of important relationships which involve the corresponding component part.

CONSTRUCTION OF A SYSTEM MODEL

Development of a general structure, combination of related component parts in the general structure, and specification of a system model for relationships among combinations of component parts in the general structure accomplish the construction of a system model.

Development of a General Structure

A general structure now is developed to serve as the basis for the construction of a system model for relationships among component parts, and to bring the global aspects of the system into focus. This general structure is formed by an informative and unifying arrangement of component parts.

The first step is to identify the components of the system. The next step is to form groups of related component parts within components. Then an ordering is arranged for components, groups within components, and component parts within groups. To the extent feasible, the arrangement should possess the desirable characteristic that a component part tends to influence only those component parts which follow it.

An example is provided by the flow process application in Table 4, which also includes component part combinations and linear relationships. In this table, Q denotes Question; and β_0, β_1, β_2, . . . , β_6 symbolize general unspecified constants in the relationships. For simplicity, the same symbols, β_0, β_1, β_2, . . . , β_5, are used in each relationship; although they are not meant to denote the same constants.

Table 4

SPECIFICATION OF A SYSTEM MODEL

USER COMPONENT*

A. User's Age: Q48

B. User's Education

1. User's highest degree: $Q50A = \beta_0 + \beta_1 (Q48)$
2. User's field of degree: $Q50C = \beta_0 + \beta_1 (Q48)$
3. User's year of degree: (Q50B)
   Not used in flow process model.

C. User's Experience

Combination: $1/2\,(Q51+Q52) = \beta_0 + \beta_1 (Q48)$

1. User's job experience: Q51
2. User's company experience: Q52

D. User's Position

1. User's kind of position
   $Q55 = \beta_0 + \beta_1(Q48) + \beta_2(Q50A) + \beta_3(Q50C) + \beta_4(1/2(Q51+Q52))$
2. User's field of position
   $Q56 = \beta_0 + \beta_1(Q48) + \beta_2(Q50A) + \beta_3(Q50C) + \beta_4(1/2(Q51+Q52))$
3. User's Military Occupational Specialty (MOS) equivalent
   (Q53 and Q57 - narrative - coded as Q57)
   Not used in flow process model.

E. User's Level

Combination:

$$1/2(Q49+Q58) = \beta_0 + \beta_1(Q48) + \beta_2(Q50A) + \beta_3(Q50C) + \beta_4(1/2(Q51+Q52)) + \beta_5(Q55) + \beta_6(Q56)$$

1. User's equivalent Government Service (GS) rating: Q58
2. Number of personnel supervised by user: Q49
3. User's type of activity (Q54)
   Not used in flow process model.

*Q denotes Question; and β_0, β_1, $\beta_2, \ldots, \beta_6$ symbolize general unspecified constants in the relationships. For simplicity, the same symbols, β_0, β_1, $\beta_2, \ldots, \beta_6$, are used for each relationship; although they are not meant to denote the same constants.

Component parts (or components) which tend to influence other component parts (components) may be called input component parts (components), and those which tend to be influenced by other component parts (components) may be called output component parts (components). Arrangement of components and component parts within components, according to an input/output point of view, facilitates the specification of a system model for relationships. It also provides insight into the system.

Combination of Related Component Parts

Groups of related component parts are combined, whenever feasible, to simplify the specification and estimation of a system model for relationships among component parts in the general structure. In addition, the combination of related component parts summarizes and simplifies the general structure. Two of the simplest types of combinations are averages and products. They keep the combination scales normalized to between -1 and 1. For the flow process example, see Table 4.

Component part combinations which tend to influence other combinations of component parts may be called input factors, and combinations of component parts which tend to be influenced by other component part combinations may be called output factors. It is both informative and suggestive to characterize combinations of component parts as input factors and output factors. One must realize, however, that statistical analysis can merely estimate and indicate the significance of a relationship. It cannot imply that the relationship is cause and effect, for this can only be accomplished by a thorough knowledge of the system.

When a more refined analysis is desired, the component part combinations could be separated.

Specification of a System Model

Once the general structure is developed and groups of related component parts are combined, it is appropriate to specify a system model for

relationships among combinations of component parts in the general structure. The terms, combination of component parts and component part combination, also are used to cover the degenerate case of a single component part (for example, Q56 in Table 4). A linear relationship among component part combinations is a mathematical expression of the variation in a given combination of component parts (Y) as a linear function, with unspecified constants, of the variations in the other component part combinations ($X_1, X_2, \ldots, X_p$).

Analysis of the general structure from an input/output point of view yields those component part combinations which are judged to be potentially related to each combination of component parts in the general structure. Only the potentially related component part combinations are included in the relationship for that combination of component parts. It is frequently both convenient and sufficiently accurate (for example, during exploratory research) to let the system model be composed of linear relationships. An example is provided by the flow process application in Table 4.

When the component parts have been properly arranged, a general structure suggests the relationships. A more refined analysis could specify additional relationships, particularly those necessitated by the separation of component part combinations.

COMPUTER SIMULATION

INTRODUCTION

Several classes of system problems, such as those where either subsystem resource allocation or subsystem dynamic interactions are to be evaluated, are not amenable to closed-form mathematical solutions. However, models for such system problems have been created, reduced to computer algorithm, and computed, providing important analytical results for systems engineers.

The technique employed is generally referred to as discrete simulation, event simulation, or process simulation. This discussion will shed light on the rationale and the steps involved, and will present computer aids for performing such simulations.

SYSTEMS ENGINEERING ANALYSIS

Engineers are system-oriented people. Most of us operate with systems where relationships between elements of the system (that is, the subsystems) are readily stated in mathematical form. Solutions to our analytical problems require that, at worst, we hire a statistician, who hires a programmer, who hires a numerical analyst to develop an algorithm that provides the significant figures required in computing the mathematical model of our system. At best, we write our own FORTRAN program using library routines to construct the system model and have the answer within a week.

For some engineers, however, systems become complicated and the models do not lend themselves to easy assembly for computation. The elements themselves may be tractable, but put together and encapsulated in the bigger black box by procedures, priorities and operational constraints at a higher system level than considered during element (subsystem) analysis, we find

ourselves in a less quantifiable, less well-ordered, less closed-form model domain. This situation reduces our ability to predict with a high degree of confidence system performance within expected ranges of operational parameters. Thus, systems engineering analysis proceeds with system model assumptions (examples being linearity of constraints or static representation of dynamic, time-phased subsystem considerations) that provide approximate results.

Discrete system simulation can be used when one cannot find other techniques for analyzing and evaluating alternative dynamic system operational schemes. That is, the model can be built with which to experiment with controlled system variables in order to apply unusual stresses beyond normal system operating ranges; or to force uncontrolled variables to such levels and for such assumed periods of time that would either be too damaging or would take too long in the real system operation, if that system actually exists. Furthermore, we can formulate subsystem interactions between functional elements of the system and relate these logically to the whole system. Such submodel formulation relieves the systems engineer of the detailed task of describing complete, closed-form system performance; however, he synthesizes the complete system model by combining submodel formulation provided by subsystem experts.

LEVELS OF SIMULATION ANALYSIS

Just where does simulation fit into a total system program? We can enumerate four distinct periods or phases in the life cycle of a system: (1) research, (2) development, (3) operation, and (4) replacement. In at least the first three, various levels of uncertainty becloud the major aspects of the tasks involved in accomplishing objectives. For example, in the research phase, great uncertainty often surrounds the very concept of system proposals. During the development of a system, many important design parameters affecting system performance present alternative means of accomplishment. In the operational phase, there are uncertainties concerning system growth

and flexibility. In all of these phases, system simulation is capable of providing program managers with analytical guidelines for selecting preferred system alternatives.

Research

System research takes the form of advances in technology along many lines. Component development, automatic programming of central computers, advanced display techniques, and responsive man-machine information query subsystems are examples of related developments upon which advances in system application depend. When research culminates, the existing system concepts are based either on the unique application of the advanced technology, or on revised concepts of data acquisition, processing, display, or management.

With success of the hypothesized system depending possibly on a yet unrealized breakthrough in some technology area, how can the conceptualized system's feasibility be demonstrated? Simulation can help predict the chance of achieving successful implementation of the concept. In effect, the concept is simulated to ascertain the feasibility of the following:

1. Reaction times required by system elements.
2. Proposed subsystem transfer functions.
3. Information content required for decision making.
4. Survivability characteristics in a hostile environment.
5. Phasing and planning compatibility.
6. Reliability goals.

The questions of concept answerable through simulation are broadly stated, looking to total system reactions to subsystem stimuli, using engineering estimates of the performance characteristics and other planning factors. Estimates of subsystem performance are probabilistically stated, usually, but are they consistent? Inconsistencies in planning factors conceived by different segments of an organization responsible for pieces of the concept

are soon shaken out by a system simulation exercise performed early in the research phase.

Development

In the development phase of the system life cycle, simulation provides valuable insights into four major aspects of the design process: (1) alternative configurations, (2) allocation of funds for total system improvement, (3) costs versus system effectiveness, and (4) policy changes versus system performance.

Once system development has begun, and plans are beginning to yield products, the system can be further analyzed by simulation. At this stage of the system life cycle, much more is known about the specifications of the subsystems. Probability distributions and parameters associated with variables are better quantifiable. The questions asked of the simulation analysis become more specific: What priority should this sensor data have as opposed to all others? How much data delay can be tolerated and still achieve effective system operation? What is the effect of better equipment maintenance policy (and increased mean time between failures) on system performance? What are the costs of Configuration A as opposed to Configuration B? What are the gains in performance between System A and System B? Where are the decision bottlenecks? What action best relieves bottleneck conditions? Do we want to relieve these bottleneck conditions?

The process of designing subsystems of a system accelerates during the development phase. Their elements and characteristics can be either described in great detail or may be estimated very confidently. Some of these characteristics, such as subsystem data transfer capacity, become critical with respect to the potential stress that the system will undergo. Detailed descriptions of these critical characteristics are parameterized in the system model during the development phase of system design. System performance can be examined while these elemental values are allowed to vary. A preferred combination of system policy and hardware characteristics can be

established from simulation analysis of several choices, measured by values of the chosen objective function.

Operation

There are many impelling reasons for simulating an operational system. These fall into the following categories: (1) system capacity limitations versus stress levels, (2) decision automation potential, (3) total system value analysis of subsystem improvement, and (4) off-line training exercises.

In the operational phase of a system's life, all of the data about all of the elements of each subsystem can be collected to any degree of refinement. Certainly, a computer system simulation model could not be built with more realism than exists in the actual system. However, computer simulation still plays an important analytic role in extending understanding of existing systems. At this stage, questions of analysis are more precisely directed to known system elements. The systems engineer asks: what is the effect on system performance of sampling sensor data at less frequent intervals, if the basic error rate frequency distribution of the sample data does not change? If present operational activity were suddenly to increase by 20%, which subsystem element would be the first to break down? Or if increased by 50%, or doubled? If man-made decisions were programmed into hardware, what would be the expected incidence of inappropriate system response? With normal system growth, what is the approximate time that present system elements would use up existing excess capacity? How can we best cope with these anticipated problems--better procedures? Better hardware? More hardware?

Summary

Simulation fits into the system analysis picture wherever uncertainty and the effects of the time dimension or the interrelationship of different elements within a system need to be better understood, and a system field experiment or exercise is too costly or impractical. Also, because the nature of complex

systems operation is known only probabilistically, the effect of random variation requires a dynamic simulation in order to examine interactions between and among subsystems.

DISCRETE SIMULATION FOR SYSTEM ANALYSIS

Developments in computer technology have broadened the scope of large, complex systems synthesis. Computers have grown in storage capacities and have increased in speeds; software designed for simulation problems now include discrete simulation systems packages; and statistical design techniques have been coupled with simulation for more effective systems analysis.

Engineers, in exploiting these new computer simulation developments, are now confronted with the necessity of understanding discrete simulation principles and techniques. Foremost in the analytical process is a requirement to structure system models that can be efficiently computerized. Engineers and computer model builders must share the burden of discrete simulation modeling.

By assuming that a system is organized as definable and important subsystems, and that relationships among these subsystems can be either formulated or described by logical conditional procedures, a basis exists for model building. To attain a feasible basis for modeling a system, specific goals--or system objectives that the system must satisfy--must be established. To achieve a realistic system model, all necessary and interesting system elements and relationships must be quantifiable, and the objective functions established to measure performance of examined system structures (that is, how well each structure achieves system goals).

System Objectives

Starting with the assumption that the system exists (even conceptually), the first step in system model building is to establish system objectives. Analysis requirements, and the structure of a simulation model, clearly

should be guided by these objectives. In simulation model-building terms, this means: list the questions to which the engineer wishes quantified answers about system performance. Proceeding from defined objectives, the engineer can develop functional block diagrams and stimulus-response lines between system elements necessary for driving all activity within the system. These diagrams help the model builder describe the constraints in the system, the possible system states produced, and the probability of achieving each state. Stimuli exogenous to the system must also be identified.

Selecting System Variables

With the aid of a computer model builder, and with established system objectives as a guide, key variables of system performance will be identified. They will be either controlled or uncontrolled with respect to the system. An objective function will be developed, expressed in terms of these variables. This is the model builder's way of computing system performance measures for objective comparisons among different structures of a system. Requirements will be established for data and for estimates of input-output functions (submodels) characterizing subsystem interactions. Descriptions of all attainable system states and the subsystem activities that produce each state complete the system description for model building.

Events of a Discrete Simulation

Decomposition of a system's operation into component steps that may (stochastically) or do (determi stically) change status of key system variables produces: (1) a list of system events, and (2) cause-and-effect expressions--equation, logical algorithm, and so forth--relating dependent and independent variables of each event, to describe the reasons that changes occur.

These events are the conditions modeled in a discrete simulation analysis. That is, the moment of change is modeled, and total system effect of that change is evaluated in a simulation of these moments. Between events, because the system is quiescent, performing normally without status change,

or undergoing discrete changes, only the independent variable time will change state. By definition, both the start and the end of a system operation step become events of a discrete simulation model.

The mathematics of each event describes independent variables whose values or states lead to possible alternatives of the dependent variable state. An isolated event is one in which dependent variables are not independent variables of other events that could occur simultaneously. By considering time and space as criteria and by reducing either or both of these reference bases, almost all system events can be ultimately defined as isolated. This essentially increases both the detail required to describe the outcome of an event and the number of events required to describe system dynamics. If sequential operations occur at different time frames and affect different functions of a system, isolated events can be developed. Parallel events (those occurring at the same time) that do not share common functions are isolated if they are statistically independent. Events sharing common functions which are not parallel are isolated if they are mutually exclusive (see Table 5). For discrete simulation computer model building, isolated events facilitate model implementation.

Table 5
EVENT ORGANIZATION

FUNCTION / TIME	Separable	Common
Separable	Isolated	Isolated if mutually exclusive
Simultaneous	Isolated if independent	Not isolated

Formulation for Simulation

A system model is formulated for discrete simulation by logically or mathematically describing events and associated variables. Events describe system actions which change the state of the system (that is, change variables of the system). Variables are the entities of the system whose characteristics, when quantified, provide state conditions whose change must be recognized in the simulation. The numeric values of these characteristics become vectors or arrays of state condition.

Variables that confront model builders are either controlled or uncontrolled in the system and its operating environment. Uncontrolled variables in the system are controllable in a simulation, possibly by probabilistic algorithms.* Some simulations will not control all controllable variables, if certain of these factors are not interesting at the moment; if experimental design dictates they need not be measured explicitly; or if they are included only to provide richness to a model (that is, provide a "realistic" model). These are generally treated as random variables.

Several computer languages are available at present to implement system simulation models. The need for specific attention to discrete simulation software that eases the burden of programming, coding and debugging system models is obvious when past history of project elapsed times is reviewed. No such review will be made here; rather, we will summarize some of the model building conveniences available for discrete simulation. These are recognized as beneficial to other classes of computer programs, but several simulation-specific systems have organized and exploited these techniques. Significant reductions of elapsed times, from system modeling to operating simulation programs, have resulted.

*This is one of the compelling reasons that simulation experiments are preferable either to field tests or experiments with actual systems.

Timing

A unique requirement for simulation systems is to organize the management of time passing as events occur. Time is an independent variable of all simulations. Good techniques to simulate time can both increase analysis accuracy and reduce computer operating time. If simulation start time is T_o and progression over time is $T_1, T_2 \ldots T_k \ldots$, then time in simulation must be monotonic increasing in (k). A model must simulate all events (i), and each occurrence (j) of event (i) at time T_m ($E^m_{i,j}$) before those at T_n if m<n; otherwise, a cascade of system interactions triggered by the dependent variables of $E^m_{i,j}$ i = 1, 2,...; j = 1, 2... that may be independent variables of $E^n_{i,j}$ will be disregarded, or, worse, erroneously simulated.**

Constraints determined by the systems engineer are used to compute model elapsed time within each event. This could be a function of system overall status at any point in a system operating cycle, of stochastic parameters, etc. Calendars of events are maintained by the simulation software, and each event is sequenced to occur in order of time preference, however determined in the model. Describing how elapsed time between system status changes will occur as event constraints is sufficient to allow software to sequence properly all events to determine realistically the effect of time on system performance.

Entity Descriptions

Simulation languages employ mathematical notation and easily understood English expressions to describe variables and their characteristics. For example, a voltage generator that is part of an automatic checkout device might be labeled VOLT and described as in Table 6. Reference to the cube of the voltage regulator could be stated in the program as CUBE (VOLT). If there are several different generators of this type, then the variable VOLT could be labeled VOLT = MANY and the quantity "MANY" be given a numeric

**The problem of interactions between and among events occurring at T_k simultaneously is ignored.

Table 6

DESCRIBING A VARIABLE

VARIABLE: VOLT	
CHARACTERISTIC	NAME
Type	KIND
Range: Upper Lower	HIGH LOW
Weight	LBS
Dimension	CUBE
Failure Rate	MTBF
Maintenance Period	CYCLE
Use	STEPS

value limiting the size of the VOLT matrix. All VOLT variables would require data specification for all defined characteristics; that is, the specifications of the VOLT components in the system deemed necessary to describe these generators' performance must be enumerated. Note that KIND might very well be given a logical value 1 for ac and 0 for dc, so that all voltage generators could be specified in a single matrix.

Because variables and characteristics that contribute to system model realism and performance measurement must be described and quantified, simulation languages provide simple means to express and relate them. Subsystem levels can be related as follows:

AGE (STAGE(SIVB))

to specify a type of automatic equipment (AGE) specifically used for a particular stage (STAGE) of the Saturn S-IVB (SIVB). Furthermore, the expression

COUNT (STAGE, SIVB (PLACE, STATE))

might be countdown time accumulated for each stage of several S-IVB's at different launch complexes and in different conditions with respect to a total countdown cycle.

Event Computations

Simulation languages not only permit direct and English-like statements that establish system variables and attributes, but event computations are also made with the following statements:

IF HIGH (VOLT) - LOW (VOLT) GR 125, THEN DO....

FAIL = EXP**RANDM*MTBF (VOLT)

Association of items into classes containing common characteristics is accomplished with set instructions. Arithmetic and logical operations can be performed on all variables temporarily grouped into sets by the dynamics of system performance. For example, queues of items awaiting future failure computed on the basis of mean-time-to-failure can be gathered in a system factor called QUEUE, automatically ranked on the earliest time to anticipated failure. Operations that examine or change sets are performed on the factor QUEUE. Simulation languages, not the model builders, worry about the bookkeeping needed to manage the fluctuating size of QUEUE.

Other common set organization procedures, such as LIFO and FIFO, are automatically controlled by the languages after the model builder specifies a rule. Usually, he specifies such set discipline by a simple mark on a data input form.

Statistical Data Computations

Use of statistical data as input to discrete simulations is also a matter of naming system variables, and of specifying data as continuous distributions, tables, or histograms. Linear interpolation is automatic between values of dependent variables. Random choice of independent variable is also permitted. Computation of probabilities for standard density functions, such as exponential, uniform, normal, Poisson, and so forth facilitate sampling procedures. For example, Figure 7 is a cumulative distribution with each point described as a pair (x, P(x)). Referring to the simulation variable table will generate a random number R, where $0 \leq R \leq 1$, and then cause an interpolation between the closest neighboring (x, P(x)) input values surrounding R = P′(x).

Most simulation results are in the form of distributions and parameters describing behavior of system elements. Stochastic representation of some system elements leads to system actions that cannot be predicted with

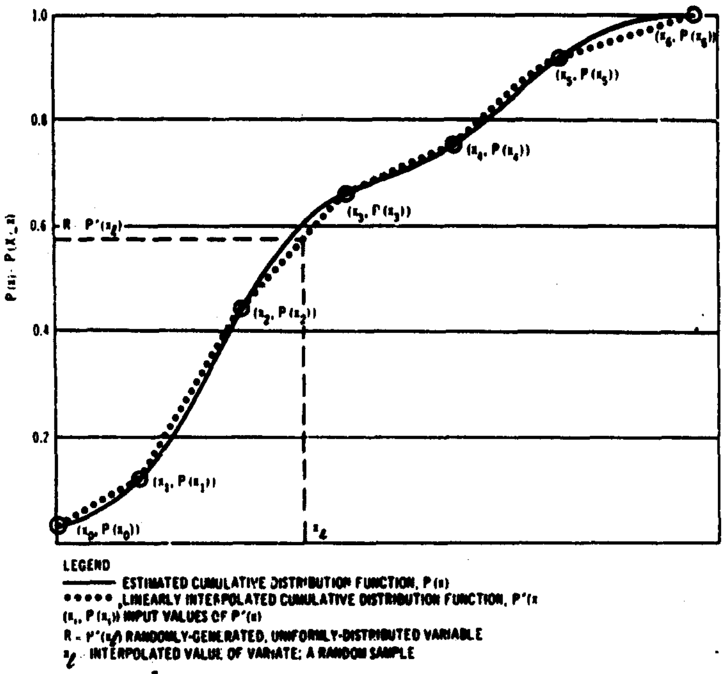

Figure 7. Cumulative Distribution Function Representation and Use

certainty. Thus, expected values, average lengths of waiting times, variances, frequency distributions, and so forth, are typical forms of simulation results. Simulation languages accomodate statistical data gathering. Simple instructions (macros) contain complete programs for integrating variables over time, computing means, variances and other statistics, and compiling data points for histogram and curve plots.

Closely associated with techniques used in simulation language to compile statistical behavior of system variables is the facility to report these statistics to the simulation analyst. Several current simulation languages provide such data automatically; others allow analysts freedom to draw output formats, designate the variable name (for example, VOLT), and map with code marks specific data. Reports then are assembled in their entirety by the simulation language according to the prescribed map.

Reference 3 presents an excellent discussion of computer simulation in general.

SYNOPSIS

In practice, discrete simulation only partially fills the void in the process of complete system analysis, because one cannot hope to optimize system performance with design parameters only through this process. This presentation, however, has shown how system engineering analysis can be better organized to achieve more rational choices among alternatives by using simulation. In fact, simulation use is proposed very early in the research phase of the system life cycle. Further improvement of models possible in the system development phase only enhances simulation applicability while there is still time to alter design parameters. Even while systems are operational, simulation is a technique that aids systems engineers to answer redesign questions involving advanced procedures, revised operating policies and unusual stress conditions.

This paper has also discussed system analysis approaches that insure better models for discrete simulation. It is important that system engineers and simulation model builders together attack system analysis and synthesis problems to insure both feasible and realistic simulations. Finally, some of the simulation language aids have been described that translate system models into efficient discrete simulation computer programs.

SYSTEM OPTIMIZATION

INTRODUCTION

In the context of this paper, a major purpose of a complete system analysis is to improve, in some sense, the system or its output. From the viewpoint of the systems engineer or the operations analyst, this improvement is accomplished through an optimization process. Thus, optimization is the process of improving a system with "the best" as a goal.

This process has some very general characteristics. It can be either subjective or objective, it can be either qualitative or quantitative, and it can be thought of as being in a closed form or as a function requiring either iteration or simulation (see Table 7). This portion of the lecture will briefly discuss these characteristics, and then illustrate a powerful method of optimizing for complex problems, with an actual example drawn from the world of incentive contracting.

Table 7
OPTIMIZATION PROCESS

	Qualitative		Quantitative	
	Closed	Open	Closed	Open
Subjective	"Best"	Voting	Statement of value	Adding or averaging values
Objective	Ordering a fixed set of alternatives	Selecting and ordering an open set of alternatives	Derivatives equal to zero	Iterative methods

OPTIMIZATION METHODS

Subjective-qualitative, or nonquantitative, methods include the following: (1) authoritative statements that this system is the "best" without proof or justification--the "salesman approach"; (2) asking others for their opinion--the "expert judgment approach"; and (3) voting in a committee--the "democratic approach". Many system decisions, if not most, are made by these techniques.

Subjective-quantitative methods include (1) the calculation of a numerical value for some system characteristic for one configuration and saying, "it only costs this much" or "it's blue isn't it?"; (2) comparison of this value with others, especially competing, systems such as "this car is cheaper than 26 models of the so-called low-priced three"; and (3) "the weighted average cost of operation is x cents per ton mile," where neither the method of weighting nor the factors averaged are made explicit.

Objective-qualitative methods include (1) the ordering of a fixed set of alternative configurations--"the best tactical fixed wing aircraft for this job is--" and (2) the ordering of an open set of alternative configurations--"the best solution to this tactical problem is to use a--," when all feasible equipment items are considered.

Objective-quantitative methods (for each independent measure of effectiveness) include the following:

1. Compute the measure for each possible configuration and select the one with the highest (or lowest) value.
2. Compute the measure for some alternatives, plot the measure for the principle variables, and select the "best" by inspection of the resulting curves.
3. State the measure as an equation (function of controllable variables and parameters).

A. If the function is differentiable, then the solution may be obtainable in closed form by setting the partial derivatives equal to zero and solving, or through the use of La Grangian multipliers.

B. If the function is not differentiable, or if the partials are complex and awkward, the procedure is to use the most suitable iterative method.

(1) Interpolation methods (Newton's Method).

(2) Linear programming.

(3) Quadratic programming.

(4) Dynamic programming.

(5) Non-linear programming.

(a) Steepest ascent based on local partial derivatives.

(b) Pure search methods.

INCENTIVE CONTRACTING EXAMPLE

In the contracting world, the basic problem is that of maximizing the fee earned as a function of the risk involved. Contracts usually call for the delivery of a number of items of a specified quality in a specified time period at a specified cost. The questions of risk and uncertainty arise in estimating the cost, quality or delivery schedule, or all three. If this uncertainty is small, contract terms probably should specify a fixed price (FP). This, in effect, makes the contractor assume all the risk, and in return permits him to make and keep any or all fees (price minus actual cost). On the other hand if this uncertainty is large, the customer may have to assume the risk in order to get a contractor to agree to do the work. In this case, a cost-plus-fixed-fee (CPFF) agreement is usually the best solution. In the case of moderate risk, the contractor may be motivated to meet performance requirements, schedules and cost estimates if his earned fee is variable and also is dependent on how well he meets the customer's goals. Thus the incentive contract was born: in its most basic form, it states that the fee earned is a function of how well the contractor performs.

To a systems engineer, this definition indicates that a mathematical function can be developed which expresses the relationships among fee, cost, performance and delivery time.

$$\text{Fee} = f\,(\text{Cost, Performance, Time})$$

$$F = f\,(C, P, T)$$

It also suggests that if such an equation can be developed, it can also be optimized. For instance, should the customer suggest an incentive contract in an RFP, it usually means that he has analyzed the work to be performed in meeting the schedule and performance specifications, and has established a set of value judgments concerning the amount of additional fee he is willing

to pay to obtain higher performance values or earlier delivery dates. This is most often construed by the contractor to mean penalties for poor performance or late delivery. In any event the contractor must also analyze the work to be performed, must estimate the uncertainties and risks involved, and must establish the amount of fee he desires for various levels of cost, performance and delivery times. The process of incentive contract negotiation then becomes one of reaching a compromise between these two estimates.

The problem of estimating the risk is equivalent to that of estimating an expected performance level, and establishing a confidence region around it for each performance factor and schedule item. If this is done and the relationships among the factors are known, the overall or total risk can be estimated in cumulative probability distribution form. To accomplish this estimate it is necessary to establish a conceptual model, develop a mathematical model within this framework, estimate the unknown parameters, and finally solve for fee as a function of the selected factors and parameters. In other words, a complete system analysis is performed.

The model chosen for this incentive contract is of the following form: earned fee is a function of cost and performance, $F = f(C, P)$. This model was chosen because of its simplicity and because it could be represented by a three-dimensional surface. The model was constrained further by reasoning that the fee should decrease as cost increases, and should increase as performance increases. Two further constraints were added for this particular case. One, the relationship between fee and cost should be piecewise linear, to correspond with the contractual concept of cost sharing (see Figure 8).

The relationship between fee and performance should be quadratic, to correspond to the belief that every increase in performance should be rewarded with an increase in fee, but at a lower rate as performance becomes higher (see Figure 9). The combination of these constraints results in a three-dimensional model as illustrated in Figure 10.

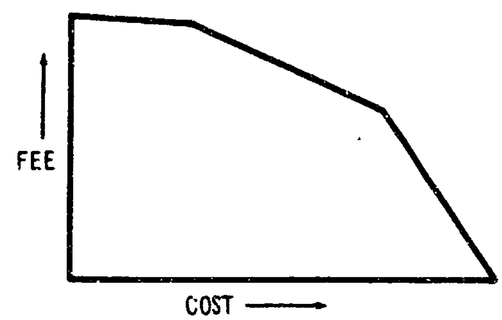

Figure 8. Fee Versus Cost Relationship

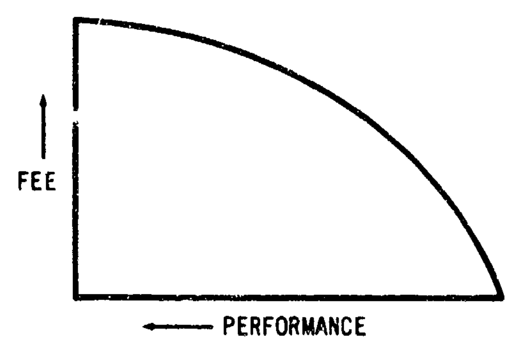

Figure 9. Fee Versus Performance Relationship

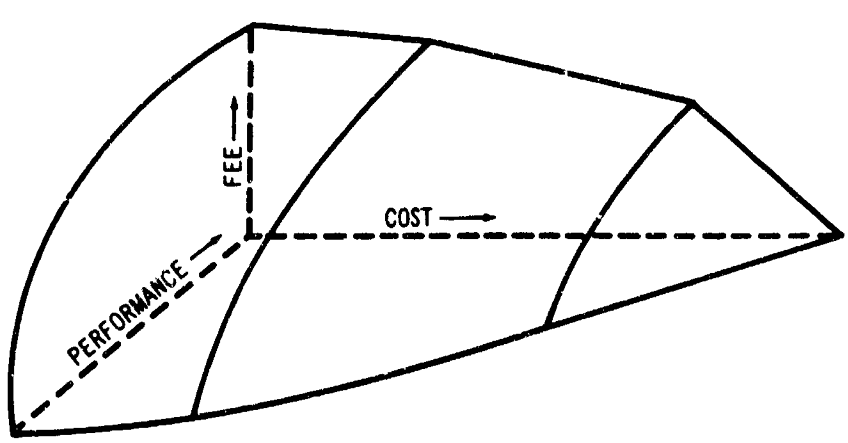

Figure 10. Fee Versus Cost and Performance Relationship

The use of this model requires that schedule and performance items be combined into a single measure of performance. This may seem to be a mixing of oranges and apples; but by recalling that late delivery may decrease the value of the system as much as, say, a degradation in some technical performance factor, this mixing becomes feasible. This feasibility is enhanced when considering that the achievement of some technical performance goal may actually cause a delay in delivery. To accomplish the definition of the performance variable, it was decided to use a weighting system based on points. The entire spectrum of performance factors, to be included in the function determining fee, was allocated one thousand points. A matrix of performance factors versus hardware end-items was formulated, and points assigned on the basis of importance to program objectives, as in Table 8.

Table 8
EQUIPMENT-PERFORMANCE MATRIX

Performance Factor		Equipment Item Number				
		1	2	3	. . .n	Total
A	1	0	8	1	x	x
	2			12	x	x
	3					
B	1	10	96	24	x	x
	2	108	13	24	x	x
.						
.						
.						
M	1	x	x	x	x	x
	2	x	x	x	x	x
Total		X	X	X	X	1000

This form of weighting is ideal in the sense that quantitative items such as delivery date, dichotomous items such as test pass or fail, and subjective items such as maintainability and flexibility, can be included in the same scale. It also permits the negotiation of the relative value of each item, separately or in combination. A review of these weights was made to avoid the inadvertant over-weighting of any particular item due to interaction effects. This so-called domino effect can be treated by assigning the points in a manner to account for these interactions.

While the performance scale was being negotiated by teams of technical experts representing both the customer and the contractor--negotiation to ensure that the customer's goals would be met and that the technical risks would be shared--the cost experts took a look at the expected total costs of the program. These negotiations produced an expected cost, called by the contracts people target cost or administrative target cost, and a rough estimate of the probability of overruns and underruns, of specified amounts or percents of target cost. These two separate but related efforts produced a qualitative and highly subjective estimate of the expected performance and cost points. One such estimate, made by the contractor in the particular case in mind, was that the performance points achieved would be about 650, or 65% performance, at a cost equal to a 15% overrun (target cost plus 15%). At the same time, the customer's estimate at this point was 80% performance at a 10% over-run. Because these two estimates did not agree, negotiation was required to settle the point.

The contractor justified his position by separately and independently estimating the probability of making the points assigned to each cell in the matrix, as shown in Table 8. Each estimate was made by the technical person responsible for doing the actual work. At the same time, an upper- and lower-bound estimate was made. This was a subjective procedure designed to correspond to the statistical procedure of establishing a confidence interval. A review of these procedures by the negotiation teams produced a

negotiated position that the most probable performance and cost region fell between 60% and 80% performance, and between 0% and 15% cost over-run.

This agreement produced a most likely region for the model; but fee dollars or percent had not been agreed to, so the exact location was still in doubt. The next and final step in specifying the exact model (specification of the unknown parameters) was accomplished by negotiating the fee dollars for each corner of this region or box (see Figure 11).

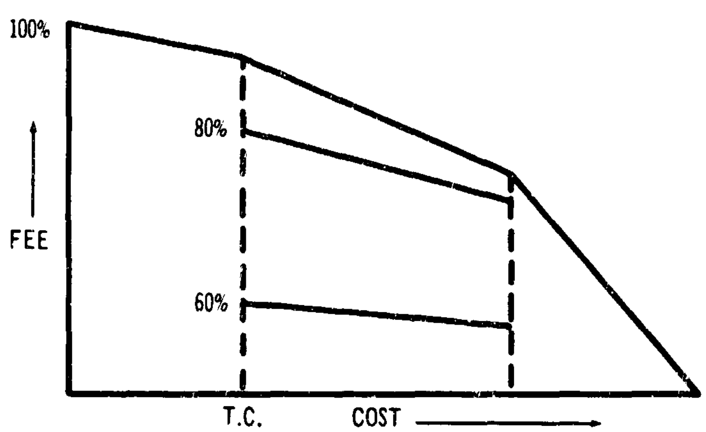

Figure 11. Negotiated Relationship

This negotiation took the form of establishing a set of dollar fees for each of the four corners which was acceptable to both parties. Once this had been accomplished, the shape of the model that would pass through these four points was determined by negotiating the maximum fee dollars for 100% performance and minimum cost, and a set of share ratios. This maximum point is very probably unobtainable, and was determined primarily by considering the effect of such a point on the renegotiation board. This point and a set of share ratios were negotiated; the share ratios are for determining the portion of any change in cost from the target cost to be borne by the customer and the contractor. In turn, the exact mathematical model was specified for this contract.

Before the proposal was submitted by the contractor, a computer model was developed for the general model which was piecewise linear in the cost-fee

plane, and quadratic in the fee-performance plane. This program was designed to accept any combination of fee, cost and performance points, and cost-share ratios; and through curve-fitting techniques, solve for the quadratic coefficients at each cost break (the point where cost-share ratio changes). These coefficients and cost-break values then completely defined the surface, and the quantitative aspects of the contract.

This computer program is, in effect, a simulation routine for determining the effect of various combinations of cost and performance on fee. In addition, the computer could and did compute such items as fee dollars per performance point per cost dollar, so that tradeoffs between cost and performance could be investigated. This program was available during the entire negotiation period, and was used by both sides to determine the effect of each proposed change. It was used to optimize the contract in the sense of assuring the customer a high probability of obtaining his desired performance, cost and delivery objectives, at the same time assuring the contractor that he would obtain a fair return for his effort.

For more detailed information on incentive contract negotiation, see References 4, 5 and 6.

Optimizing by use of a computer simulation of a mathematical model, to provide estimates of system performance for systematically changed values of the controllable variables and/or parameters, is probably the most powerful optimizing technique available for the complete analysis of highly complex systems. It is particularly appropriate in the conceptual development phases of a large system. When kept up to date with system design changes and newly discovered relationships, it provides the most powerful tool for managing and controlling the procurement phase, and assures that the final system meets its technical objectives on time and within an acceptable cost range.

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4. NASA Incentive Contracting Guide, Second Edition. National Aeronautics and Space Administration Report NPC 403, January 1965.

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APPENDIX

COMPLETE SYSTEM ANALYSIS: A GRAPHIC SUMMARY

Figures A-1 through A-8 graphically summarize complete system analysis, and Figures A-9 through A-16 graphically summarize complete system design.

COMPLETE SYSTEM ANALYSIS: FRAMEWORK FOR UTILIZATION OF COMPUTER SIMULATION IN ANALYSIS AND OPTIMIZATION OF A COMPLEX SYSTEM

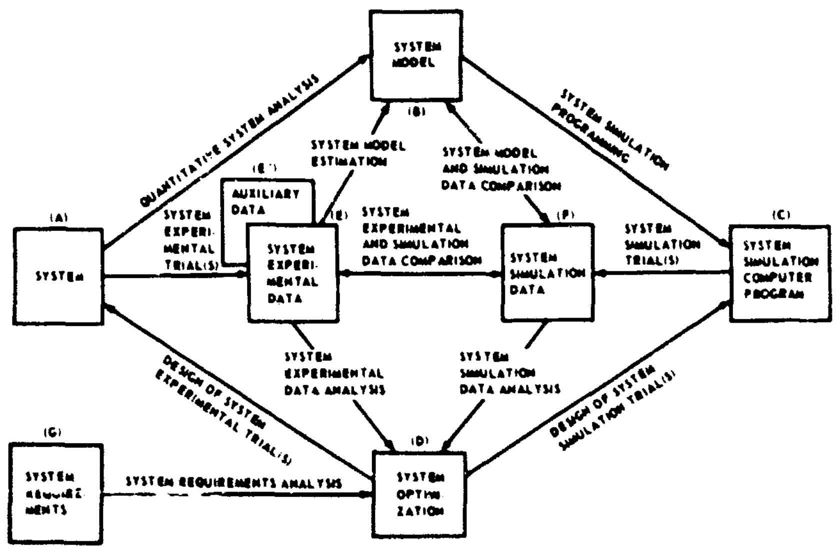
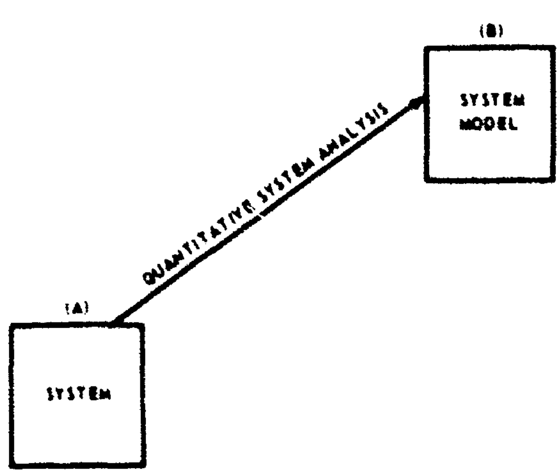


Figure A-1

QUANTITATIVE SYSTEM ANALYSIS



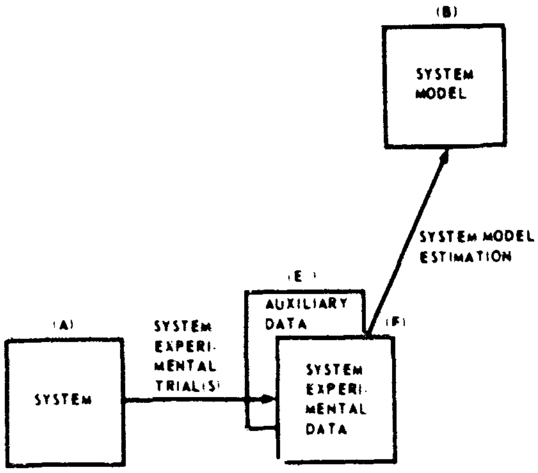
- QUANTITATIVE SYSTEM ANALYSIS DEVELOPS A SYSTEM MODEL (MATHEMATICAL REPRESENTATION OF THE SYSTEM) BY TRANSFORMING QUALITATIVE SYSTEM ELEMENTS INTO NUMERICAL FORM, AND CONSTRUCTING A MODEL FOR RELATIONSHIPS AMONG SYSTEM COMPONENT PARTS.

- TRANSFORMATION OF QUALITATIVE SYSTEM ELEMENTS INTO NUMERICAL FORM IS ACCOMPLISHED BY ARRANGING THE ELEMENTS INTO AN INFORMATIVE DETAILED (LOCAL) STRUCTURE, AND THEN ASSOCIATING A MEANINGFUL NUMBER WITH EACH ELEMENT.

- CONSTRUCTION OF A MODEL FOR RELATIONSHIPS AMONG SYSTEM COMPONENT PARTS IS ACCOMPLISHED BY ARRANGING THE COMPONENT PARTS INTO AN INFORMATIVE GENERAL (GLOBAL) STRUCTURE, AND THEN SPECIFYING THE GENERAL FORM OF MEANINGFUL RELATIONSHIPS AMONG COMPONENT PARTS

Figure A-2

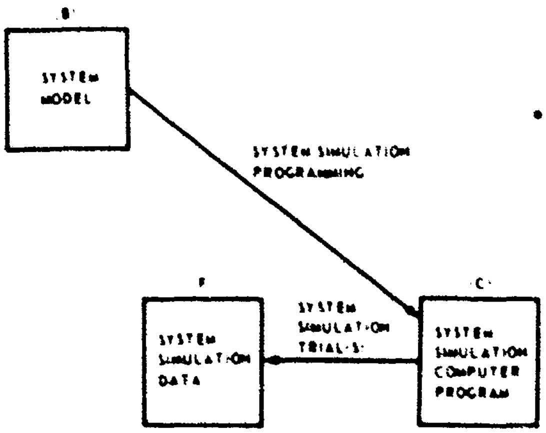
SYSTEM EXPERIMENTAL TRIAL(S) AND MODEL ESTIMATION



- <u>A SYSTEM EXPERIMENTAL TRIAL</u> PRODUCES SYSTEM EXPERIMENTAL DATA.
- <u>SYSTEM MODEL ESTIMATION</u> PRODUCES ESTIMATES OF UNSPECIFIED CONSTANTS IN THE GENERAL FORM OF RELATIONSHIPS IN THE SYSTEM MODEL, AND A PRELIMINARY, BUT INSUFFICIENT, EVALUATION AND VALIDATION (POSITIVE CHECK) OF THE SYSTEM'S REPRESENTATION BY THE SYSTEM MODEL.

Figure A-3

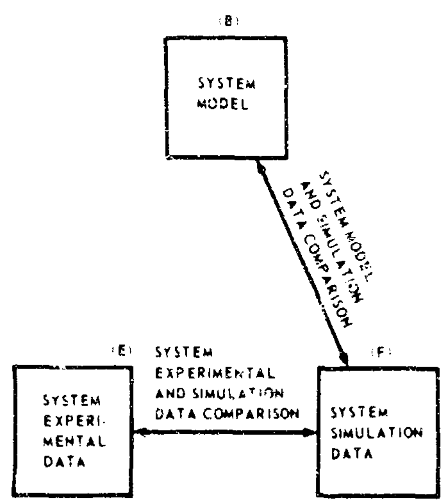
SYSTEM SIMULATION PROGRAMMING AND TRIAL(S)



- <u>SYSTEM SIMULATION PROGRAMMING</u> TRANSLATES THE SYSTEM MODEL (MATHEMATICAL REPRESENTATION OF THE SYSTEM) INTO A SYSTEM SIMULATION COMPUTER PROGRAM (COMPUTER REPRESENTATION OF THE SYSTEM).
- <u>A SYSTEM SIMULATION TRIAL</u> PRODUCES SYSTEM SIMULATION DATA.

Figure A-4

SYSTEM MODEL. SIMULATION DATA, AND EXPERIMENTAL DATA COMPARISON

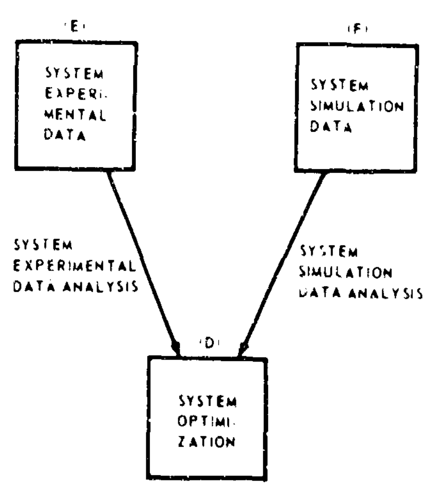


- SYSTEM MODEL AND SIMULATION DATA COMPARISON PROVIDES AN EVALUATION AND VALIDATION (POSITIVE CHECK) OF THE SYSTEM MODEL'S REPRESENTATION BY THE SYSTEM SIMULATION COMPUTER PROGRAM

- SYSTEM EXPERIMENTAL DATA AND SIMULATION DATA COMPARISON PROVIDES AN EVALUATION AND VALIDATION OF THE SYSTEM'S REPRESENTATION BY THE COMBINATION OF SYSTEM MODEL AND SIMULATION COMPUTER PROGRAM, AND AN INDIRECT EVALUATION AND VALIDATION OF THE SYSTEM'S REPRESENTATION BY THE SYSTEM MODEL GIVEN THAT THE MODEL'S REPRESENTATION BY THE SIMULATION COMPUTER PROGRAM HAS BEEN VALIDATED

Figure A-5

SYSTEM EXPERIMENTAL AND SIMULATION DATA ANALYSIS

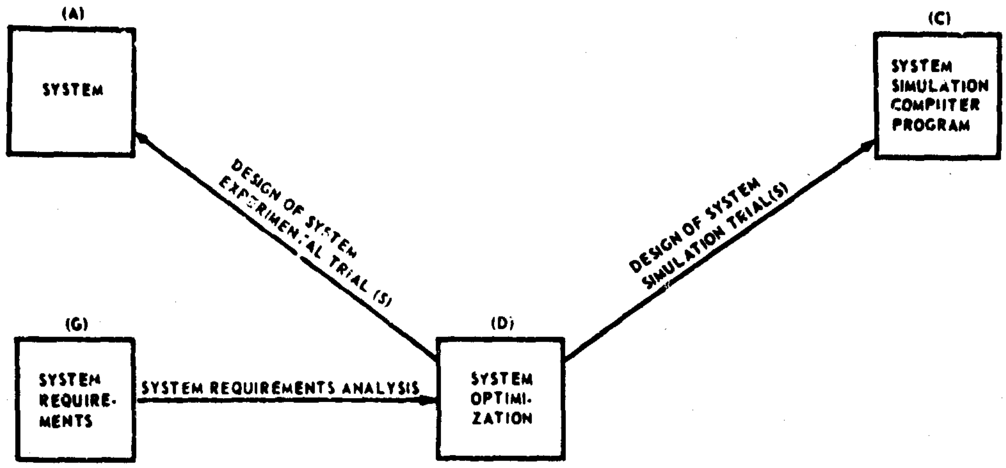


- SYSTEM EXPERIMENTAL AND SIMULATION DATA ANALYSIS CHARACTERIZE AND EVALUATE THE SYSTEM AND SUGGEST MODIFICATION OF THE SYSTEM FOR SYSTEM OPTIMIZATION ACHIEVEMENT OF SUFFICIENT IMPROVEMENT

- EVALUATION OF THE SYSTEM IS IN TERMS OF SYSTEM CRITERIA AND CONSTRAINTS (FOR EXAMPLE, THOSE OF COST OR EFFECTIVENESS)

Figure A-6

SYSTEM OPTIMIZATION, DESIGN OF SYSTEM EXPERIMENTAL AND SIMULATION TRIALS, AND SYSTEM REQUIREMENTS ANALYSIS



- SYSTEM OPTIMIZATION MODIFIES THE SYSTEM, AND APPLIES THE APPROPRIATE PORTIONS OF COMPLETE SYSTEM ANALYSIS TO THE MODIFIED SYSTEM – IN AN ITERATIVE MANNER, UNTIL THE ACHIEVEMENT OF SUFFICIENT SYSTEM IMPROVEMENT.

- DESIGN OF SYSTEM EXPERIMENTAL AND SIMULATION TRIALS AIDS THE IMPLEMENTATION OF SYSTEM OPTIMIZATION.

- SYSTEM REQUIREMENTS ANALYSIS PROVIDES A BASIS FOR SYSTEM OPTIMIZATION, AND DESIGN OF SYSTEM EXPERIMENTAL AND SIMULATION TRIALS

Figure A-7

COMPLETE SYSTEM ANALYSIS: FRAMEWORK FOR UTILIZATION OF COMPUTER SIMULATION IN ANALYSIS AND OPTIMIZATION OF A COMPLEX SYSTEM

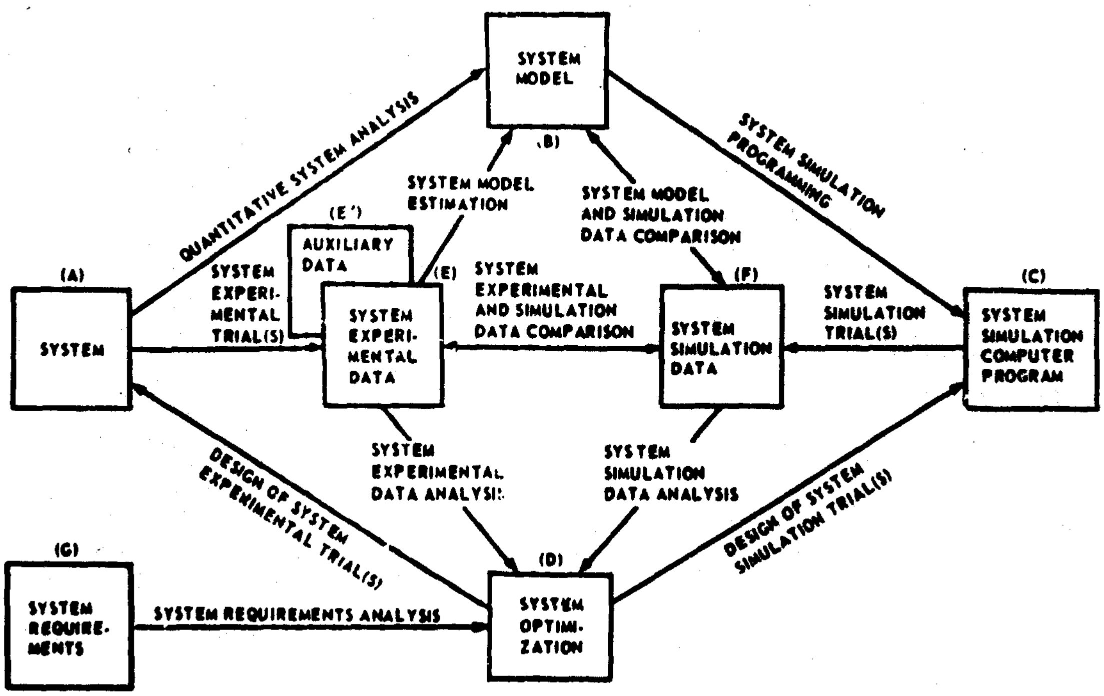


Figure A-8

COMPLETE SYSTEM DESIGN: FRAMEWORK FOR UTILIZATION OF COMPUTER SIMULATION IN DESIGN OF A COMPLEX SYSTEM

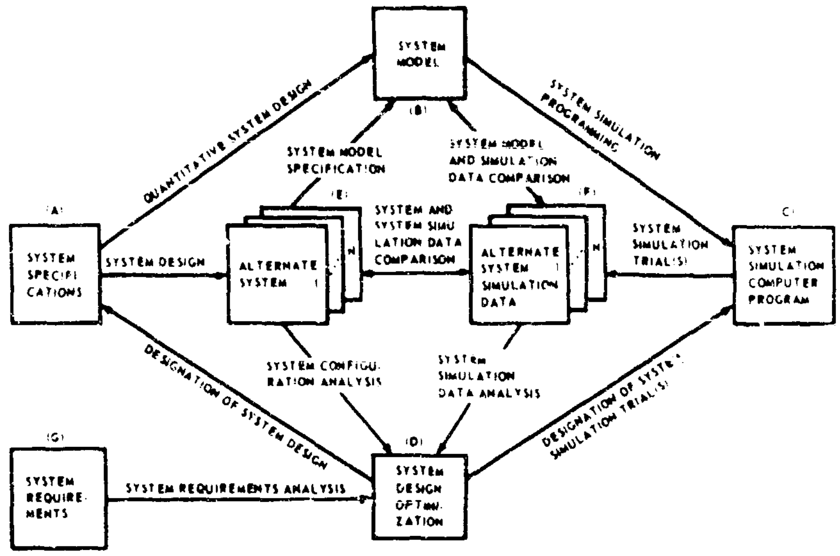
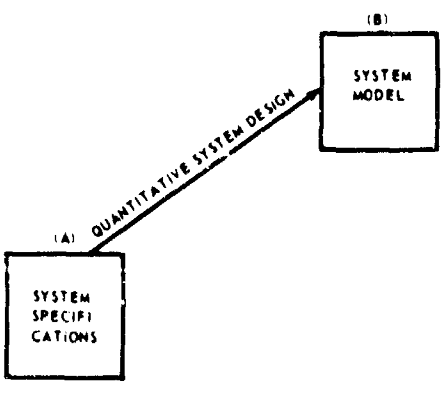


Figure A-9

QUANTITATIVE SYSTEM DESIGN



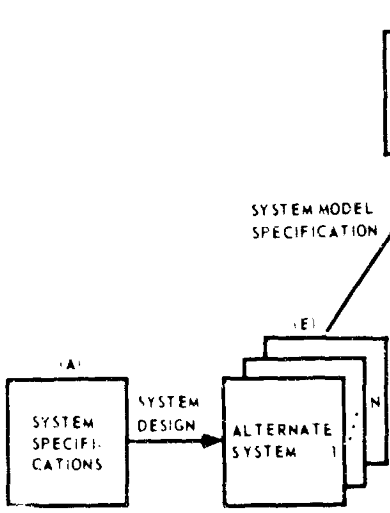
- QUANTITATIVE SYSTEM DESIGN DEVELOPS A SYSTEM MODEL (MATHEMATICAL REPRESENTATION OF THE SYSTEM), WHICH IS SUFFICIENTLY GENERAL TO COVER EACH ALTERNATE SYSTEM, BY TRANSFORMING QUALITATIVE SYSTEM SPECIFICATION ELEMENTS INTO NUMERICAL FORM, AND CONSTRUCTING A MODEL FOR RELATIONSHIPS AMONG SYSTEM SPECIFICATION COMPONENT PARTS

- TRANSFORMATION OF QUALITATIVE SYSTEM SPECIFICATION ELEMENTS INTO NUMERICAL FORM IS ACCOMPLISHED BY ARRANGING THE ELEMENTS INTO AN INFORMATIVE DETAILED (LOCAL) STRUCTURE, AND THEN ASSOCIATING A MEANINGFUL NUMBER WITH EACH ELEMENT

- CONSTRUCTION OF A MODEL FOR RELATIONSHIPS AMONG SYSTEM SPECIFICATION COMPONENT PARTS IS ACCOMPLISHED BY ARRANGING THE COMPONENT PARTS INTO AN INFORMATIVE GENERAL (GLOBAL) STRUCTURE, AND THEN SPECIFYING THE GENERAL FORM OF MEANINGFUL RELATIONSHIPS AMONG COMPONENT PARTS

Figure A-10

SYSTEM DESIGN AND MODEL SPECIFICATION



- SYSTEM DESIGN PRODUCES ALTERNATE SYSTEMS 1, ..., N, WHICH IMPLEMENT SYSTEM SPECIFICATIONS.
- SYSTEM MODEL SPECIFICATION PRODUCES FOR EACH ALTERNATE SYSTEM, VALUES OF UNSPECIFIED CONSTANTS IN THE GENERAL FORM OF RELATIONSHIPS IN THE SYSTEM MODEL, AND A PRELIMINARY, BUT INSUFFICIENT, EVALUATION AND VALIDATION (POSITIVE CHECK) OF THE SYSTEM'S REPRESENTATION BY THE SYSTEM MODEL

Figure A-11

SYSTEM SIMULATION PROGRAMMING AND TRIAL(S)

- SYSTEM SIMULATION PROGRAMMING TRANSLATES THE SYSTEM MODEL (MATHEMATICAL REPRESENTATION OF THE SYSTEM) INTO A SYSTEM SIMULATION COMPUTER PROGRAM (COMPUTER REPRESENTATION OF THE SYSTEM)
- A SYSTEM SIMULATION TRIAL PRODUCES SYSTEM SIMULATION DATA FOR EACH ALTERNATE SYSTEM

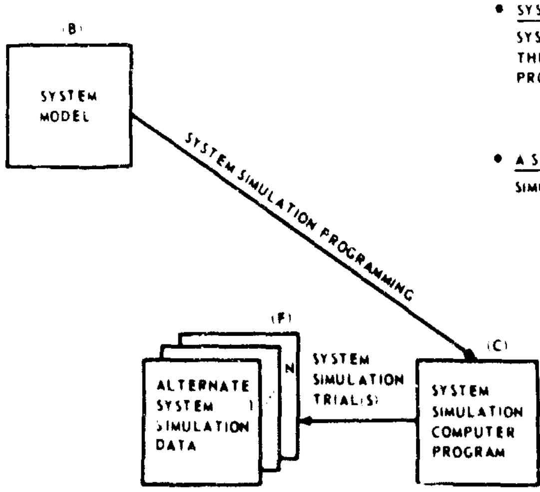
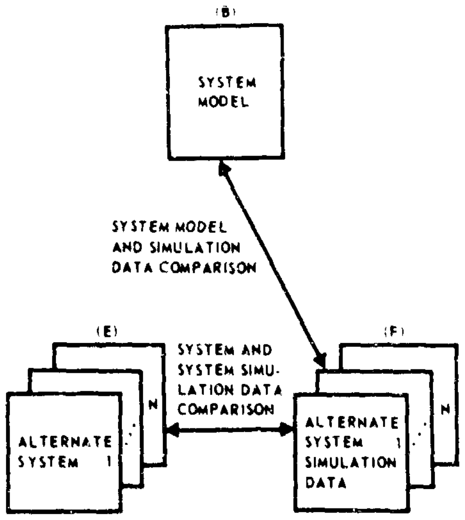


Figure A-12

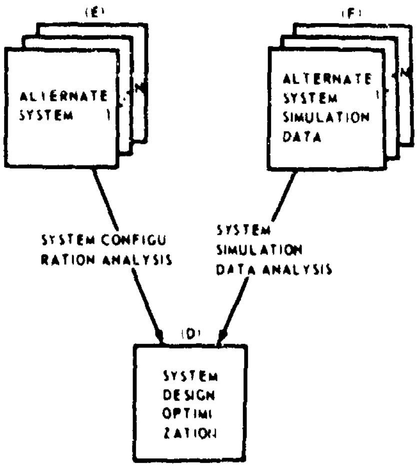
SYSTEM MODEL, SYSTEM SIMULATION DATA, AND SYSTEM COMPARISON



- SYSTEM MODEL AND SYSTEM SIMULATION DATA COMPARISON PROVIDES, FOR EACH ALTERNATE SYSTEM AN EVALUATION AND VALIDATION (POSITIVE CHECK) OF THE SYSTEM MODEL'S REPRESENTATION BY THE SYSTEM SIMULATION COMPUTER PROGRAM
- SYSTEM AND SYSTEM SIMULATION DATA COMPARISON PROVIDES, FOR EACH ALTERNATE SYSTEM, AN EVALUATION AND VALIDATION OF THE SYSTEM'S REPRESENTATION BY THE COMBINATION OF SYSTEM MODEL AND SIMULATION COMPUTER PROGRAM, AND AN INDIRECT EVALUATION AND VALIDATION OF THE SYSTEM'S REPRESENTATION BY THE SYSTEM MODEL, GIVEN THAT THE MODEL'S REPRESENTATION BY THE SIMULATION COMPUTER PROGRAM HAS BEEN VALIDATED

Figure A-13

SYSTEM CONFIGURATION AND SIMULATION DATA ANALYSIS

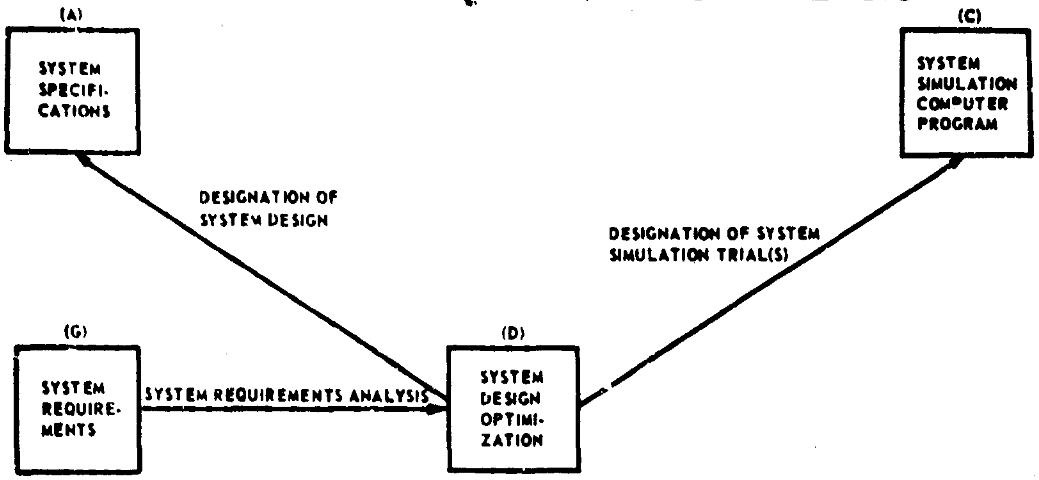


- SYSTEM CONFIGURATION AND SIMULATION DATA ANALYSIS

  CHARACTERIZE AND EVALUATE EACH ALTERNATE SYSTEM AND SUGGEST MODIFICATION OF THE SYSTEM DESIGN FOR SYSTEM DESIGN OPTIMIZATION (ACHIEVEMENT OF SUFFICIENT IMPROVEMENT)
- EVALUATION OF EACH ALTERNATE SYSTEM IS IN TERMS OF SYSTEM CRITERIA AND CONSTRAINTS (FOR EXAMPLE THOSE OF COST OR EFFECTIVENESS)

Figure A-14

SYSTEM DESIGN OPTIMIZATION, DESIGNATION OF SYSTEM DESIGN AND SIMULATION TRIAL(S), AND SYSTEM REQUIREMENTS ANALYSIS



- SYSTEM DESIGN OPTIMIZATION MODIFIES THE SYSTEM DESIGN, AND APPLIES THE APPROPRIATE PORTIONS OF COMPLETE SYSTEM DESIGN TO THE MODIFIED DESIGN – IN AN ITERATIVE MANNER, UNTIL THE ACHIEVEMENT OF SUFFICIENT IMPROVEMENT.
- DESIGNATION OF SYSTEM DESIGN AND SIMULATION TRIAL(S) AIDS THE IMPLEMENTATION OF SYSTEM DESIGN OPTIMIZATION.
- SYSTEM REQUIREMENTS ANALYSIS PROVIDES A BASIS FOR SYSTEM DESIGN OPTIMIZATION, AND DESIGNATION OF SYSTEM DESIGN AND SIMULATION TRIAL(S).

Figure A-15

COMPLETE SYSTEM DESIGN: FRAMEWORK FOR UTILIZATION OF COMPUTER SIMULATION IN DESIGN OF A COMPLEX SYSTEM

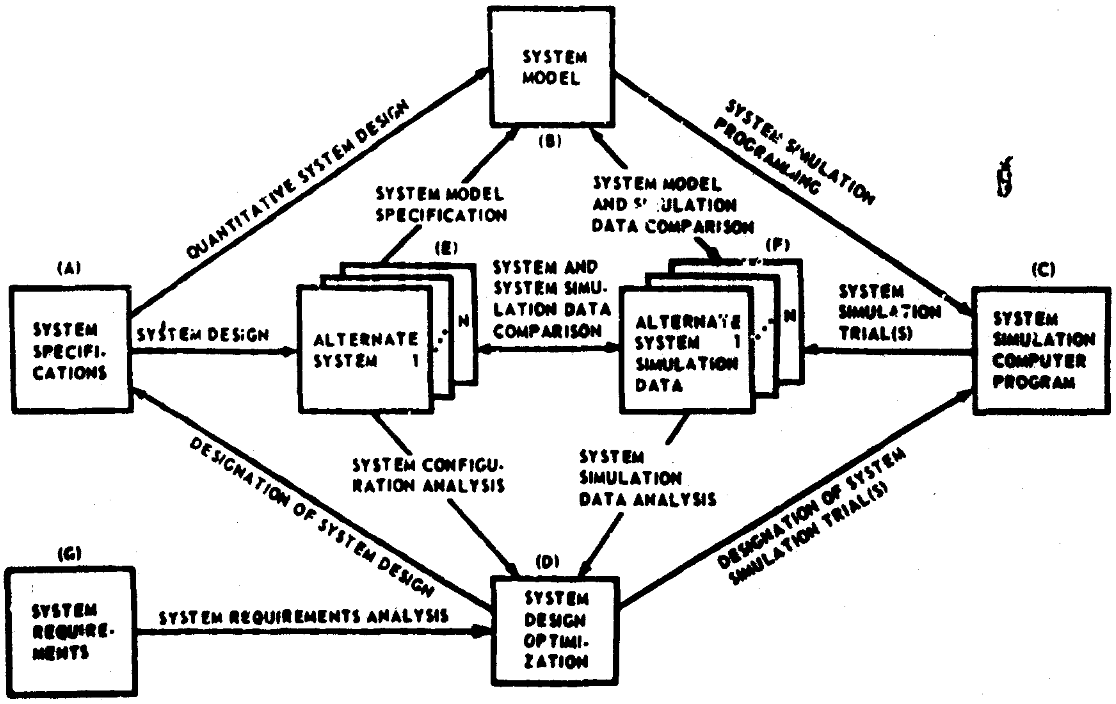


Figure A-16